Exploration Strategies of Coordinated Multi-Robot System: A Comparative Study

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ABSTRACT

Environment Exploration is the basic process that most of Multi Robot Systems applications depend on it. The exploration process performance depends on the coordination strategy between the robots participating in the team. In this paper the coordination of Multi Robot Systems in the exploration process is surveyed, and the performance of different Multi Robot Systems exploration strategies is contrasted and analyzed for different environments and different team sizes.

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1. INTRODUCTION

A multi-robot systems (MRS) is a set of mobile robots that may have similar or different capabilities where they are connected through a wireless sensor network to share the sensory information with reconfigurable sensing capabilities [1]. The essential goal of MRS is to achieve a complete task in a shorter time than the required time for achieving the same task using a single robot, since in MRS the task is performed simultaneously [2]. MRS has a number of advantages over a single robot system such as higher fault-tolerance, consolidation of the overlapped information [3, 4], prohibition of task execution by other robots [5], [6], reduction of energy consumption which leading to longer communication time during the task achievement [7], [8].

Recently MRS have been used in several applications that are dangerous to the human such as post disaster relief, military applications, search and rescue, surveillance, cleaning, mine clearing [9]-[12], etc. In such applications robots should make a decision whether to search new tasks or establish cooperative interactions to achieve their individual and collective goals [4], [13], [14].

Most of MRS applications depend primarily on the exploration of the environment in a minimum time, and the map of the environment is generated to form the MRS exploration process. MRS exploration process encounters several challenges that affect its production. These challenges are such as limitations in the environment that may force robots to move together, robot interference with each other or the redundancy due to missing of shared information [15].

During MRS exploration process, it is necessary for each robot to have enough information about the explored areas of the environment, so the robots can plan their paths and coordinate their actions. A robot can individually explore a different areas of the environment, but without any coordination it may be explore

the same area explored by other robots, block other robots, interpose other robots sensor readings, etc. The absence of coordination in MRS leads to a waste of exploration effort and time. Therefore, coordination between robots in MRS exploration is necessary to improve the exploration efficiency [15], [16].

The coordination is an essential task of the MRS exploration and so the system performance (execution time and system utility) is affected by its quality [13]-[16]. Coordination in MRS exploration is used to complete the overall task assigned to the MRS team, merge the obtained information by several robots, deal with limited communication, assign tasks to individual robots, specify a set of rules, interact to each individual robots, and overcome the interferences between the robots such that the coordination can be achieved more efficiently at global level [16]-[19].

In spite of a lot of development has been done in MRS exploration many challenging issues are still present. These issues include cooperation control, concurrent localization, mapping, collision avoidance, task planning, communication among robots, coordination, navigation and exploration, etc. As an example, Figure 1 shows that three robots tries to explore the environment and navigate to their goal locations. While Robot 3 can navigate to its goal, ignoring the remaining robots, Robots 1 and 2 need to coordinate so as not to cross the narrow doorway simultaneously [20]. Most of previous studies in this point focus on the coordination between individual robots to decrease exploration time, but only few papers focus on how collaborations between robots affect the exploration task itself [12], [21], [22].

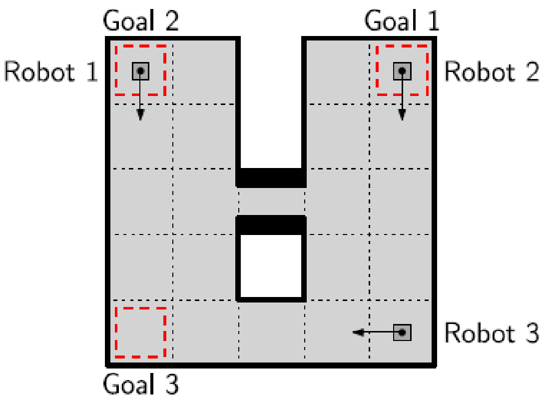


Figure 1. An example of simple navigation task

In this paper the coordination of MRS exploration is studied and a set of common recently used algorithms are presented and compared for a set of different team sizes and different environment structures. The paper is organized as it follows. A review of coordination in MRS is discussed in section 2, while the problem of exploring an unknown environment is described and formulated in section 3. The multi-robot exploration algorithms are discussed in section 4, a comparison between the performance of coordination strategies is showed and analyzed in section 5, and finally our work is concluded with suggestion for future works is presented in section 6.

2. THE MRS COORDINATION TASKS

Task coordination in MRS has been divided into three categories according to the architecture of the robots team.

2.1. The decentralized coordination architecture

In this architecture there is no central control robot and all the robots are equal with respect to control and are completely autonomous in the decision making process. It is also called distributed architecture in which each robot in the team is responsible for creating its individual mapping. Individual mapping information are exchanged between robots when they meet each other in order to build a complete map model. The decentralized coordination responds to dynamic environments in a suboptimal way [23]. The decentralized coordination has been implemented in various applications of MRS exploration such as [24]-[34]. The hierarchy of decentralized approach is shown in Figure 2.

2.2. The centralized coordination architecture

In centralized coordination architecture, there is a central control robot (leader) that has the ability to communicate with all other robots, in order to share the global information about the environment and robots. So it is responsible for mapping by collecting data from other robots. This architecture performs well for a small number of robots and run faster than decentralized coordination, but it becomes inefficient for large number of robots due to the information losses and higher communication overhead. This communication overhead may lead to communication failure and other uncertainties. The centralized architecture also produces a highly vulnerable system if the central control robot malfunctions and the entire team is disabled unless there is an alternative robot [2], [35]. There are a lot of studies belonging to the centralized architecture in MRS exploration such as [36]-[40]. The hierarchy of centralized approach is shown in Figure. 3.

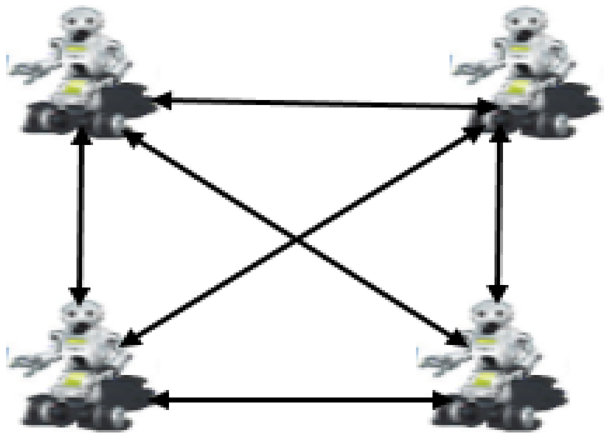


Figure 2. The Decentralized Approach Hierarchy

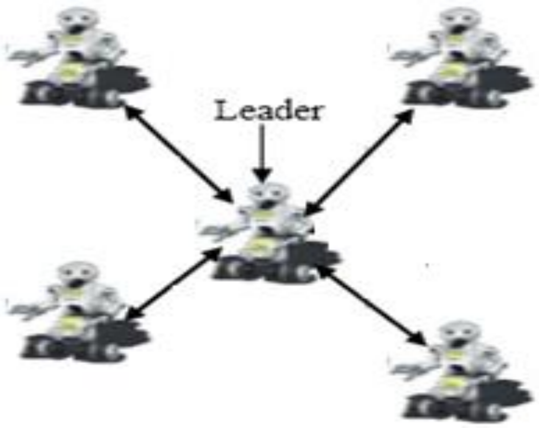


Figure 3. The Centralized Approach Hierarchy

2.3. The hybrid coordination architecture

The Hybrid coordination is an intermediate between the centralized architecture and the decentralized architecture [39]. The control process is achieved using one or more local central control robots. This situation leads to the organization of robots into clusters where each cluster is responsible for performing sub-tasks individually in a centralized manner [41]-[44]. The hybrid coordination provides more robust solutions and able to influence the entire team’s actions through global goals and plans [10], [23], [31], [45], [46].

3. THE MRS EXPLORATION OF UNKNOWN ENVIRNMENTS

The MRS can be used to explore all the regions of an environment to gather information, acquire a graphical representation, detect all the unknown place and finally build the global environment map [47]. The global environment map can be built by collecting local maps of the explored areas by each robot in the MRS. The MRS exploration is ended when the global environment map is presented. The environment map can be represented as graphs (Voronoi diagram, Visibility graph), cells (occupancy grids), polygons or trees (graph without cycles) [4], [21], [12], [47].

3.1. The problem description

The MRS exploration problem is defined as the problem of exploring an environment occupied by a set of obstacles, using a set of identical mobile robots. The four main components that affect the performance of this process are the environment, obstacles, set of robots and the exploration algorithm.

3.1.1. Environment

An environment is considered as a finite two-dimensional space with environmental boundary and it can be represented as cell based map or graph based map. In the Cell-Based map, the environment to be explored can be divided into similar cells. During the exploration process, each cell has a specific state from four states [4]: unexplored, free, wall, and frontier. The unexplored cell has not been visited by any robot,

the free cell is open and visited by at least one robot. The wall cell is occupied by an obstacle while the frontier cell is detected as a free space and is not visited by any robot and it separates the free space region and the unexplored region. In the Graph-based map, the environment is considered as a graph consisting of edges and vertices. This graph is unknown apriori where no edges and no vertices are known [7], [22].

3.1.2. Obstacles

The environment to be explored is occupied by a set of randomly, stationary and distributed obstacles with shapes and positions which are either known or unknown [36].

3.1.3. Mobile robots

A team of mobile robots performs the exploration task. These team robots may be in a similar structure (Homogeneous robots) or in a different structure (heterogonous robots). These robots can freely move from one cell to any one of its neighbors depending on some local information about the neighbor robots or the neighbor cells [1], [21].

3.1.4. Exploration algorithms

At every time step, the exploration algorithm chooses one of the frontier cells to be the next target for a robot based on its distance and the size of the environment to be explored at the current step. Exploration algorithms also update the existing map by the new information and assign a particular goal to robots using a defined cost function. The shortest path from the robots to the goals are then found [5]. Finally, the robots are navigated along the paths. A set of common exploration algorithms will be discussed in detail in section 4.

3.2. The problem formulation

The MRS exploration problem is considered as a repetitive task assignments. At each step, a robot $r_i \in= \{R_1, R_2, \dots \dots \dots, R_M\}$ is assigned to a goal $g_j \in \{G_1, G_2, \dots \dots \dots, G_T\}$ with minimum exploration time. The robot $r_i \in R$ must travel $L_i \in \{l_1, l_2, \dots \dots, l_m\}$ distance to reach the goal g. The exploration time is approximated by [48]. The following formula for traveling Berlin reaches the destination as shown in Equation (1).

$$L_i = max\{l_1, l_2, \dots \dots, l_m\}, \quad i = 1,2, \dots \dots .., m. \tag{1}$$

The objective is to find a sequence of trajectories $\zeta^{opt} = \left(\zeta_i^{opt} \middle| i = 1,2, \dots \dots ., N\right)$, among all possible trajectories $\zeta = (\zeta_i | i = 1,2, \dots \dots .., N)$, that have a minimum expected mean time of the exploration environment as shown in Equation (2). Where ζ_i and ζ_i^{opt} are trajectories of the i^{th} robot, T time needed to traverse R and the formula as shown in Equation (3).

$$\zeta^{opt} = argmin_\zeta \mathbb{E}(T|\zeta) \tag{2}$$

$$\mathbb{E}(T|\zeta) = \sum_{t=0}^{\infty} tp(t) \tag{3}$$

Where $p(t)$ is the probability density function when a prior information about objects is available. The $p(t)$ is considered to be the ratio of the area A_t^ζ newly measured at time t when the robots follow the trajectories ζ and, the area of the whole environment the robots operate A_{total}, when the prior information is not available. The following formula for probability density as shown in Equation (4).

$$\mathrm{P(t)} = \frac{A_t^\zeta}{A_{total}} \tag{4}$$

Therefore Equation 2 can be rewritten as show in equation (5).

$$\zeta^{opt} = argmin_\zeta \mathbb{E}(T|\zeta) = argmin_\zeta \sum_{t=0}^{\infty} t\, A_t^\zeta \tag{5}$$

Assumptions:

i. Each robot initially has no information about other robots and the environment except the relative distances with other robots.
ii. All robots have the same geometrical sizes equal to size of a grid cell.
iii. Each robot is able to communicate with the environment with no delay.
iv. All robots can move upward, downward, leftward, and rightward only.

4. MULTI-ROBOT EXPLORATION ALGORITHMS

Many exploration strategies exist, four methods are studied within the presented exploration framework, and the following paragraph gives an overview of these strategies.

4.1. The frontier based exploration algorithm

The key idea behind a frontier based exploration algorithm is to gain new information about an environment and navigate to the boundary between explored and unexplored territories at the time of mapping and navigation [47], [49]. When a robot navigates to a frontier cell, it will incorporate more of the space covered by the path into mapped territory. If the robot does not incorporate the entire path at one time, then a new frontier will always exist further along the path. This frontier separates the known and unknown area and provides a new destination for exploration. Navigating to a successive frontier points enables the exploration of unseen areas adding the information to the map, so the robot can increase its knowledge about the environment [49]. Figure 4 and Figure 5 represents a summary of the used search algorithm [47].

```
While ( Unexplored areas exist &
    !no_frontier_with_enough_size)
DO
    Read current sensor information
    Update the map with the obtained data
    Determine new goal candidates
        If ( No frontier found OR
            !The goal is reached)
            Return to the common Station
    Assign the goals to the robots
        If ( No assigned frontier )
            Go back to the base.
        If (overlapping with another robot)
            Take a random step.
    Plan paths for the robots.
    Choose the best frontier.
    Move the robots towards the goals.
```

Figure 4. The Frontier based exploration algorithm

```
While ( Unexplored areas exist &
    !no_frontier_with_enough_size)
Repeat
For each explorer agent DO
    Initialize explorer
    Explore environment for a time
    IF a rendezvous point is reached
        OR a parent is in range THEN
            Send information to parent
    END
END
For each relay agent DO
    Initialize relay
    IF a rendezvous point is reached
        OR a child is in range THEN
        Receive data from child agent
    END
    IF a rendezvous point is reached
        OR a parent is in range THEN
            Send data to parent agent
    END
END
```

Figure 5. The Role based exploration algorithm

4.2. The role based exploration algorithm

The role-based exploration algorithm is used to address the problem of limited communication in MRS exploration for static environments [17], [27], [50]. It is considered as a communication and planning protocol that enables MRS to construct a global map and plan their next movements. Robots are moved together in a mobile network and share relevant information for the team [21]. The MRS team forms a predefined rigid hierarchal tree which is manually constructed before the robots enter the environment. Each robot may be in one of the following three states, the first one is the **Base station** that is the root of the tree. The second is the **Explorers**, which explore the environment as possible and return back to rendezvous points at pre-arranged schedule. The third is the **Relays** that share information about the environment between their children and parent nodes to ensure that they have the same knowledge about it. A summary of the procedure is presented in Figure 5 [17], [50].

4.3. The leader follower exploration algorithm

This algorithm focuses only on the role of the team rather than the environment structure. The roles can be changed according to the distance to the corridors and the detection results. A robot may be the leader if the algorithm recognizes a frontier as a corridor, and the other robots will be set as followers or room-explorers [9]. The followers consider two factors, the first one is the **Cost**, which is the sum of path cost

V_j^i from robot i to the frontier j, and rotation cost when the robot makes a rotation to reach the target frontier and the other is the **Frontier utility,** for the R_i robot to the frontier $\psi(t)$, there will be $Reward_{\psi(t)}^{R_i}$. For the followers, the reward is shown in equation (6) and equation (7).

$$Reward_{\psi(t)}^{R_i} = Utility - Cost_j^i = U_j - (C_{path(i,j)} + C_{orintation(i,j)}) \quad (6)$$

$$= U_j - (\beta V_j^i + \gamma * O_j^i) \quad (7)$$

Where β is constant factor and O_j^i is the orientation of the robots to the target points and $O_j^i \in [0, \pi]$. In this way, the optimizing decision model of task assignment can be given as shown in equation (8).

$$\pi_{opt} = argmax_j \sum_j Reward_{\psi(t)}^{R_i} \quad (8)$$

Where π_{opt}, is the optimal decision solution of task assignment [9]. The details of this algorithm is given in Figure 6 and Figure 7.

Input: A grid map and the laser data of robots.
Output: an arrangement of robots frontiers
Build the map with the frontiers and the laser data.
Evaluate the labels m of frontier j^m .
Compute the cost V_j^i for each robot i to reach frontier j^m.
While there is any frontier j^m which is labeled corridor (m =1) without a target robot
Determine a robot i for a frontier j^m which satisfy the role model below
$i^* = argmin_i V_j^i$
End while
While there is any robot i left without a target frontier j which label m is 0
Determine a robot i for a frontier j^m for the role model according to the optimal decision model
$(i^*, j^*) = argmax_{i,j}(V_j^m - b.V_j^i - g.O_j^i)$
Reduce other frontiers' utilities as the laser's range of robot i can reach.
End while

Figure 6. The Leader follower exploration algorithm

Step 1. Subtract the smallest entry in each row from all the entries of its row.
Step 2. Subtract the smallest entry in each columns from all the entries of its column.
Step 3. Draw lines through rows and columns so that all the zero's entries.
Step 4. Test for optimality:
If zero line = n then
An optimal assignment of zero's is possible
Exist.
Else IF zero line < n then
Proceed to Step 5.
Step 5. Determine the smallest entry not covered by any lines.
Subtract this entry from each uncovered row
Add it to each covered column.
Return to Step 3.

Figure 7. The Hungarian algorithm

4.4. The hungarian algorithm

The Hungarian method is an optimization algorithm that solves the robot-task assignment. The assignment can be written in a form of the $n \times n$ matrix C, where the element $C_{i,j}$ represents the length of the path from the i^{th} robot position to the goal j^{th}. The Hungarian algorithm finds the optimal assignment for the given cost matrix C. The algorithm initially assumes that the number of goals are equal to the number of robots, in case they are not equal, an imaginary goals or robots can be added and assigned to a fixed cost and they are skipped during the exploration process. A summary of the procedure is shown in Figure 7 [48].

5. THE SIMULATION RESULTS

In order to compare the above listed MRS exploration algorithms, MRESim is used as an exploration framework [47], [5]. The simulator assumes perfect localization and noise-free sensor data [27], [17]. A set of experiments is performed on the three different maps with various sizes and structures as described in Figure 8. In this simulation we have taken in consideration the complexity of the map as an important factor in the evaluation of these algorithms. The Simple map in Figure 8(a). describes the case of a big room with four obstacles represented as a black squares. The map in Figure 8(b). represents a slightly structured environment. The map in Figure 8(c). represents a real building with many separated rooms.

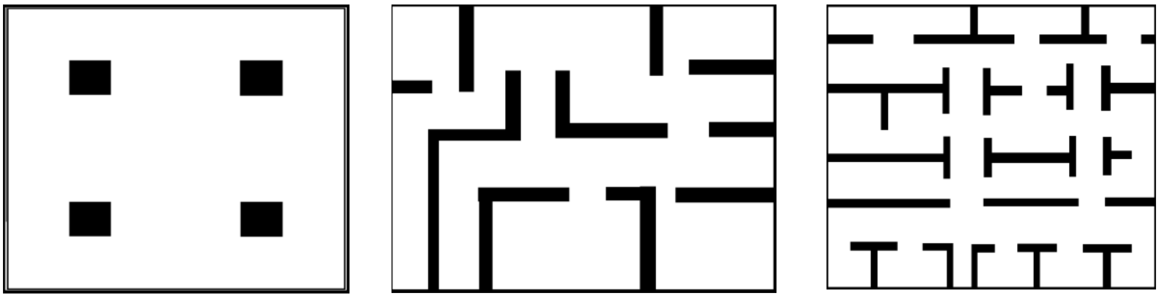
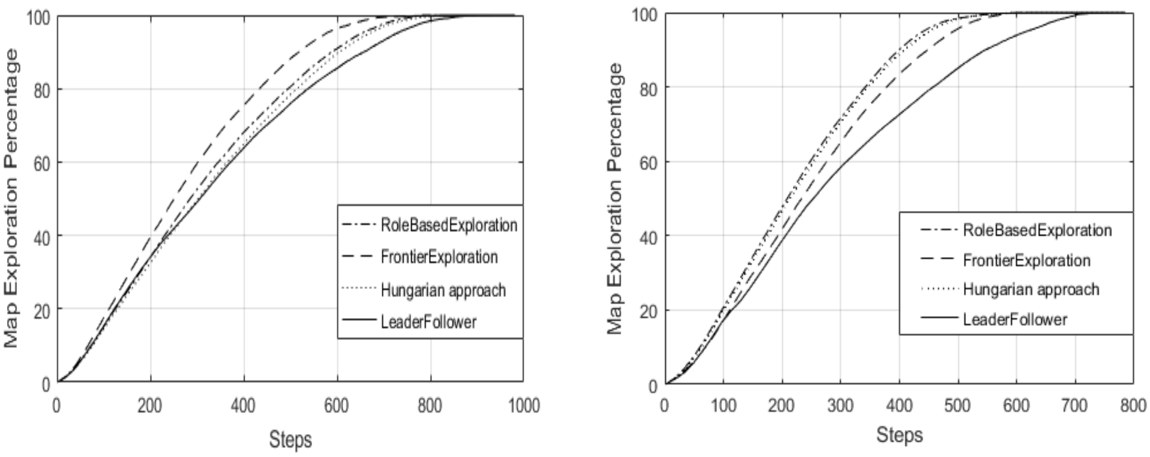


Figure 8. (a) Simple Map, (b) moderate Map, and (c) complex Map

Each environment will be modeled as an occupancy grid of 100 X 100 cells. All the algorithms are tested to cover the whole environment by a team of identical MRS. In order to get a near accurate evaluation results, these experiments will be implemented using different number of robots, two robots and four robots. All the simulations are examined on the same hardware with a core-i5 processor on 3.8 GHz, 8 GB RAM running x86 64 windows. The total number of runs are thus (4 exploration algorithms)*(3 environment maps)*(2 team size configurations)*(average of 3 runs for each experiment) = 72 runs.

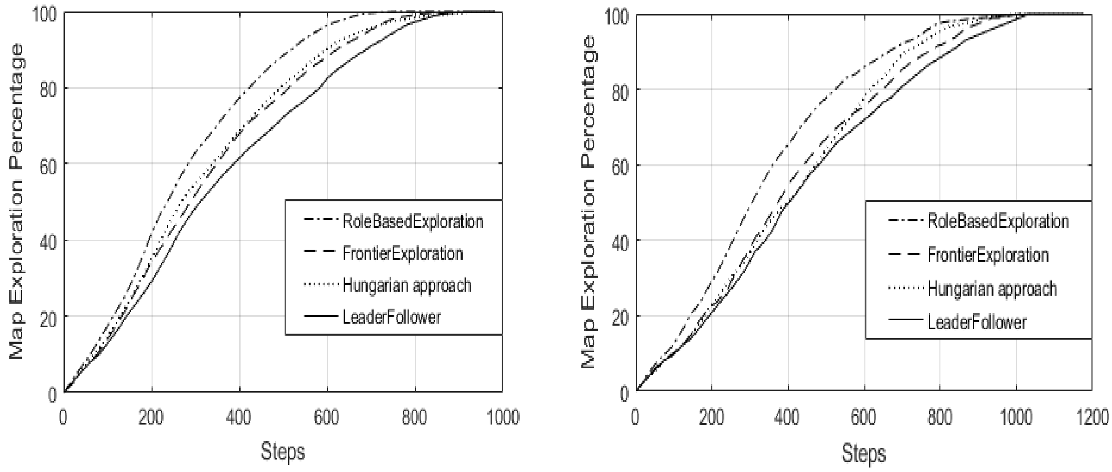
For the Simple map environment, the simulation results for all algorithms for different team sizes (2 robots and 4 robots) are shown in Figure 9. The simulation results indicate that the four algorithms give approximately the same results except the leader follower algorithm which has a slightly different behavior. This difference can be estimated as 5% for 2 robots team size and frontier based has small difference than the others, but it is the best one as shown in Figure 9(a). The leader follower algorithm has the worst behavior (14.8% worse than role based for 4 robots), due to inefficient distribution localization of the robots at the start step and sometimes the followers do the same thing that the explorers do. The hungarian and role based approaches are the best two approaches in case of 2 robots as shown in Figure 9(b).



(a) (b)

Figure 9. The Small Map Results for (a) 2 robots team size, (b) 4 robots team size

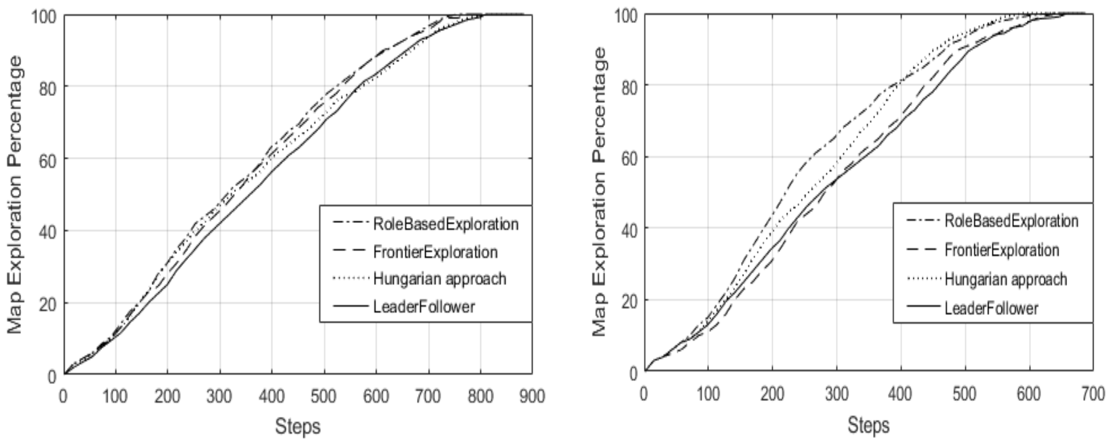
The same experiment is tested for the moderate map described in Figure 8(b) and the results are plotted as shown in Figure 10. The results of this experiment indicates that the four exploration algorithms are very close to each other when using 4 robots. The role based algorithm yields better results followed by Hungarian method as shown in Figure 10(a) and Figure 10(b) respectively. There is a slightly difference in Figure 10(a) where this difference clearly appears in two approaches: the role based and the leader follower algorithms. The leader follower which is 13.2% worse than the role based for 2 robots and 8.3% for 4 robots.



(a) (b)

Figure 10. Moderate Map Exploration (a) using 2 Robots, (b) using 4 Robots

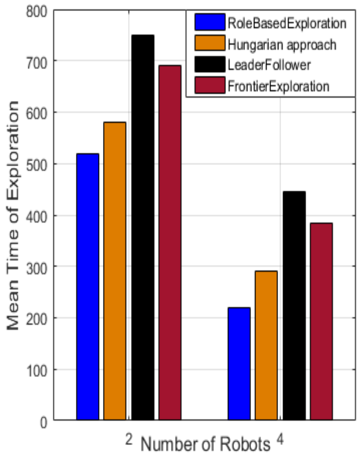
Finally the same experiment is tested for a more complex environment as described in Figure 8(c) and the simulation results are plotted in Figure 11. The performance of the exploration algorithms for a team of 2 robots is very close to each other as shown in Figure 11(a) and Figure 11(b) the leader follower exploration algorithm yields the worst performance followed by frontier approach. The best results are achieved by the role based algorithm followed by Hungarian in moderate map and the complex map which even outperforms the role based algorithm in some cases.



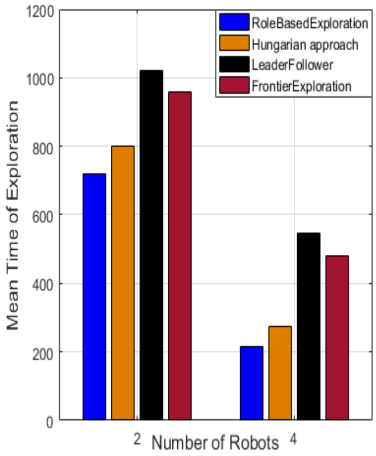
(a) (b)

Figure 11. Complex Map Exploration (a) using 2 Robots, (b) using 4 Robots

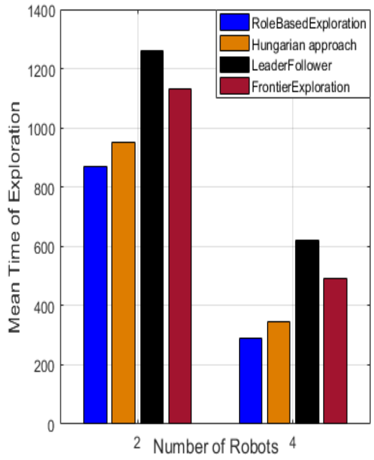
The relation between the team size and the mean time of exploration is identified by comparing the robots trajectories for all algorithms as shown in Figure 12. The simulation results show that the role based algorithm has less exploration mean time compared to the other algorithms for all cases of the three environments and team sizes. Figure 12 shows that the exploration time decreases by increasing the team size. For the same team size, the exploration time is decreased as the complexity of the environment is decreased. This results from the fact that the obstacles in the complex environment limits the detecting ranges of each robot.



(a)



(b)



(c)

Figure 12. Exploration time mean vs. robot team scale in the Moderate Map.
(a) Simple map, (b) Moderate map, (c) Complex map

6. CONCLUSION AND FUTURE WORKS

In this paper, different coordinated MRS exploration algorithms are presented, and its performance are analyzed and compared for different team sizes and different environments. Role based exploration algorithm yields a better results than the other used algorithms followed by Hungarian. In the future we can use the role based exploration algorithm as the main exploration algorithm for the design of a framework for task coordination in MRS. More efforts to increase the number of simulation runs to ensure more accurate statistical results. The role based algorithms may be implemented in real-time applications.

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